

Application and Performance Analysis of a Successive Convexification Algorithm to Mars 2020 Entry Trajectory Design

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The Entry, Descent, and Landing (EDL) nominal trajectory significantly impacts mission performance and robustness. In recent years, Successive Convexification (SCvx) has emerged as a promising approach for real-time trajectory optimization, using onboard computational resources while accommodating complex operational constraints. Integration of the SCvx algorithm with Program to Optimize Simulated Trajectories II (POST2) provides a computationally efficient framework for EDL reference trajectory optimization. Furthermore, coupling SCvx with high-fidelity flight mechanics tools like POST2 facilitates comprehensive analysis of EDL system-level performance and robustness. This work presents the integration of the SCvx algorithm with POST2. To ensure consistency and validate the integration approach, similar environment models are employed for both trajectory optimization using SCvx and POST2 simulation. The integration is demonstrated through the generation of a three degree-of-freedom Mars hypersonic entry nominal trajectory using SCvx, which subsequently guides a hypersonic entry vehicle within the POST2 simulation environment.

I. Nomenclature

ρ	=	atmospheric density, kg/m^3
r	=	radial distance from the center of the planet, m
v	=	planet-relative velocity, m/s
γ	=	planet-relative flight-path angle, deg
ψ	=	planet-relative azimuth angle, deg
ϕ	=	latitude, deg
θ	=	longitude, deg
σ	=	bank angle, deg
$\dot{\sigma}$	=	bank rate, deg/s
L	=	lift acceleration, m/s^2
D	=	drag acceleration, m/s^2
C_L	=	lift coefficient
C_D	=	drag coefficient
m	=	mass, kg
Ω	=	planet rotation rate, rad/s
g	=	gravitational acceleration, m/s^2
S_{ref}	=	reference area, m^2
$\mathbf{x}$	=	state vector
$\mathbf{p}$	=	parameters
h	=	altitude, m
t	=	time, s

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Ψ	=	terminal constraints
c, b, α, β	=	polynomial coefficients
P_m, Q_n	=	polynomials of degree m and n , respectively
Subscripts		
0	=	initial
f	=	final

II. Introduction

Over the years, landing precision requirements for Entry, Descent, and Landing (EDL) missions have become increasingly stringent. Future human exploration missions demand landing precision on the order of meters, with EDL vehicles required to deliver payloads safely and precisely in close proximity to existing ground assets. To perform EDL efficiently, vehicles must dissipate significant energy aerodynamically to minimize fuel requirements for soft pin-point landing at desired target locations while respecting operational constraints such as heat load and structural loading limits. Several guidance schemes have been studied for EDL applications in the literature, including analytical, numerical, and convex predictor-corrector approaches[1],[2]. Polynomial guidance, a computationally efficient method providing smooth, feasible trajectories using polynomial equations, has been successfully applied on Mars during the Mars Science Laboratory and Mars 2020 missions and studied for powered descent and landing guidance[3]. More recently, guidance schemes employing lossless convexification have been developed for fixed final-time powered descent maneuvers[4]. Some studies have explored onboard uncertainty quantification for robust powered descent guidance by leveraging parallel processing capabilities of radiation-hardened high-performance computing elements currently under development[5].

In recent years, the Successive Convexification (SCvx) algorithm has gained significant attention for trajectory optimization, providing computationally efficient solutions while considering multiple operational constraints. Previous studies have applied SCvx to hypersonic entry[6] and powered descent guidance[7], incorporating various operational constraints typical EDL vehicles encounter, including maximum heat rate, total heat load, maximum sensed accelerations, and maximum tilt angle. However, most literature studies examine SCvx in stand-alone simulations using lower fidelity models than the flight simulation tools employed in real-life mission design and analysis.

The entry phase presents particular challenges as uncertainties in atmosphere, entry interface states, and aerodynamics can significantly affect EDL performance. Entry guidance has traditionally been determined using analytical or numerical predictor-corrector techniques [8]. Recent studies have also considered convex predictor-corrector guidance for achieving desired crossrange and downrange targets. In contrast to powered descent guidance, SCvx applications for hypersonic entry remain relatively scarce in the literature. A recent study that applied SCvx to determine hypersonic entry reference trajectories aimed at minimizing velocity before parachute deployment while satisfying operational constraints. Previous Mars missions, such as M2020, employed range control to minimize downrange and crossrange errors. Applying SCvx to determine hypersonic reference trajectories targeting desired downrange and crossrange would benefit EDL missions. Unlike velocity magnitude minimization, targeting desired crossrange may require bank reversals, making SCvx's ability to determine optimal bank profiles particularly valuable. SCvx can enable flight mechanics tools to determine entry reference trajectories using reasonable computational resources.

Program to Optimize Simulated Trajectories II (POST2) [9] is a flight mechanics simulation tool used for numerous missions, including several Mars missions from Mars Pathfinder through Mars 2020 (M2020), as well as DAVINCI, Dragonfly, OSIRIS-REx, and others. POST2 simulates EDL flight using high-fidelity models encompassing aerodynamics, atmosphere, mass properties, multi-body dynamics, Guidance, Navigation, and Control (GNC), onboard navigation errors, and terrain. In addition, POST2 is also used to perform software-in-loop testing of the onboard GNC algorithms. Leveraging SCvx's computational efficiency to compute reference trajectories in POST2 enables evaluation of reference trajectory performance within the overall EDL system context. Additionally, POST2's uncertainty modeling capabilities allow assessment of trajectory optimization robustness using SCvx via Monte Carlo simulations.

This work focuses on integrating the SCvx algorithm with POST2 and evaluating EDL performance and robustness. To demonstrate this integration, we consider a Mars hypersonic entry flight simulation, similar to the range control portion of the M2020 trajectory [10]. The primary objective is demonstrating successful SCvx algorithm integration within POST2. For accurate comparisons, the POST2 entry simulation employs models with identical fidelity to those used for trajectory optimization. Additionally, this work presents POST2 Monte Carlo simulation results that demonstrate the robustness of the SCvx algorithm using the developed interface. The paper is organized as follows: Section III discusses the optimization problem solved using the SCvx algorithm. Section IV presents the high-level SCvx

algorithm and its POST2 integration. Section V presents nominal and Monte Carlo trajectories simulated in POST2 using bank profiles obtained from SCvx trajectory optimization. Finally, Section VI provides conclusions of this work.

III. Problem Formulation

This section discusses the dynamic model along with the atmospheric and aerodynamic surrogate models used in this work. This is followed by the discussion of the optimization problem setup used in this work to determine the desired hyper-sonic entry trajectory using the SCvx algorithm.

A. Dynamic Model

This work employs the equations of motion that govern atmospheric flight around a spherical planet as shown below [11]:

$$\begin{aligned}
 \dot{r} &= v \sin \gamma \\
 \dot{\theta} &= \frac{v \cos \gamma \sin \psi}{r \cos \phi} \\
 \dot{\phi} &= \frac{v \cos \gamma \cos \psi}{r} \\
 \dot{v} &= -D - g \sin \gamma + \Omega^2 r \cos \phi (\sin \gamma \cos \phi - \cos \gamma \sin \phi \cos \psi) \\
 \dot{\gamma} &= \frac{1}{v} \left[L \cos \sigma + \left(\frac{v^2}{r} - g \right) \cos \gamma + 2 \Omega v \cos \phi \sin \psi \right] \\
 &\quad + \frac{1}{v} \left[\Omega^2 r \cos \phi (\cos \gamma \cos \phi + \sin \gamma \sin \phi \cos \psi) \right] \\
 \dot{\psi} &= \frac{1}{v} \left[\frac{L \sin \sigma}{\cos \gamma} + \frac{v^2}{r} \cos \gamma \sin \psi \tan \phi - 2 \Omega v (\tan \gamma \cos \psi \cos \phi - \sin \phi) \right] \\
 &\quad + \frac{1}{v} \left[\frac{\Omega^2 r}{\cos \gamma} \sin \psi \sin \phi \cos \phi \right]
 \end{aligned} \tag{1}$$

where r is the radial distance of the vehicle from the center of the planet, θ is the longitude, ϕ is the latitude (angle between the equatorial plane and the vehicle position vector), v is the planet-relative velocity, γ is the planet-relative flight-path angle, and ψ is the planet-relative azimuth angle measured clockwise in the local horizontal plane from the north. σ is the bank angle, which is the rotation angle of the vehicle about the relative velocity vector, positive with the right-wing down. Ω is the planet's rotation rate about z-axis. L and D are the lift and drag aerodynamic accelerations, respectively. The lift and drag accelerations are computed as shown below:

$$L = \frac{\rho v^2 C_L S_{\text{ref}}}{2m} \tag{2}$$

$$D = \frac{\rho v^2 C_D S_{\text{ref}}}{2m} \tag{3}$$

where m and S_{ref} are the mass and the reference area of the vehicle, respectively. C_L and C_D are the lift and drag coefficients. ρ is the atmospheric density.

B. Atmosphere and Aerodynamic Surrogate Models

This work models the atmospheric density using a rational polynomial function of the form:

$$\ln(\rho(h)) = \frac{P_m(h)}{Q_n(h)} \tag{4}$$

where $\rho(h)$ is the atmospheric density as a function of altitude h , and $P_m(h)$ and $Q_n(h)$ are polynomials of degree m and n , respectively as shown below:

$$P_m(h) = c_0 + c_1 h + c_2 h^2 + c_3 h^3 + \dots + c_m h^m \tag{5}$$

$$Q_m(h) = b_0 + b_1 h + b_2 h^2 + b_3 h^3 + \dots + b_m h^m$$

The polynomials are differentiable with respect to altitude. The aerodynamic forces acting on the entry vehicle are characterized by the lift and drag coefficients, which are functions of multiple variables including velocity, angle of attack, and atmospheric conditions. In this work, the lift coefficient C_L and drag coefficient C_D are modeled using polynomials as functions of velocity in the form:

$$C_L(v) = \sum_{i=0}^k \alpha_i v^i = \alpha_0 + \alpha_1 v + \alpha_2 v^2 + \dots + \alpha_n v^n \quad (6)$$

$$C_D(v) = \sum_{i=0}^k \beta_i v^i = \beta_0 + \beta_1 v + \beta_2 v^2 + \dots + \beta_n v^n \quad (7)$$

where v is the velocity, k is the polynomial order, and $\{\alpha_i\}$ and $\{\beta_i\}$ are the polynomial coefficients determined through least-squares regression. These polynomial surrogate models replace computationally expensive aerodynamic database interpolations with simple algebraic evaluations, enabling efficient trajectory propagation and smooth derivatives for the optimization while maintaining sufficient accuracy.

C. Optimization Problem Formulation

This section presents the optimization problem solved in this work using the successive convexification:

$$\min_u J = \int_{t_0}^{t_f} u^2 dt \quad (8)$$

subject to:

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \sigma, \mathbf{p}), \quad \mathbf{x}(t_0) = \mathbf{x}_0$$

$$\dot{\sigma} = u$$

$$\Psi(\mathbf{x}(t_f), t_f) = 0$$

$$\sigma \in [\sigma_{\min}, \sigma_{\max}]$$

$$u \in [\dot{\sigma}_{\min}, \dot{\sigma}_{\max}]$$

$$t_0 \text{ is fixed, } t_f \text{ is free}$$

Here, the cost function aims to minimize the bank rate, which is the control parameter. The optimization problem needs to satisfy the equations of motion presented in Equation (1). In addition, this problem considers the bank angle (σ) as an additional state. The initial state and initial time for this problem are prescribed. The final time is free. The bank angle and the bank rate are constrained to be within their corresponding minimum and maximum values. The optimization problem considers the final radius, latitude, longitude, velocity and azimuth to be fixed. The Ψ function captures these constraints on the final states in Equation (8). Constrained latitude and longitude also fixes the downrange and crossrange of the vehicle at the final time, which is considered to be the end of the range control in this work. The final altitude constraint allows the subsequent EDL phases such as the parachute deployment, separation events and the powered descent to have enough altitude margin. The end of the range control in the previous Mars missions is triggered by a velocity trigger and therefore this problem constraints the final velocity. In addition, constraining the azimuth orients the heading of the vehicle toward the target, which is typically done in the heading alignment phase after the range control in Mars EDL missions. However, having a constraint like this at the end of the range control allows the vehicle's reference trajectory fly full lift up during the heading alignment phase leaving more margin for the feedback control if needed. The optimization problem presented in Equation 8 is a non-linear, non-convex problem. The following section discusses the SCvx algorithm, which is used to solve this problem in this work.

IV. POST2 - SCvx

This section first discusses the SCvx algorithm at a high-level for completeness of the paper. This discussion is followed by the brief summary of how the SCvx is integrated with POST2.

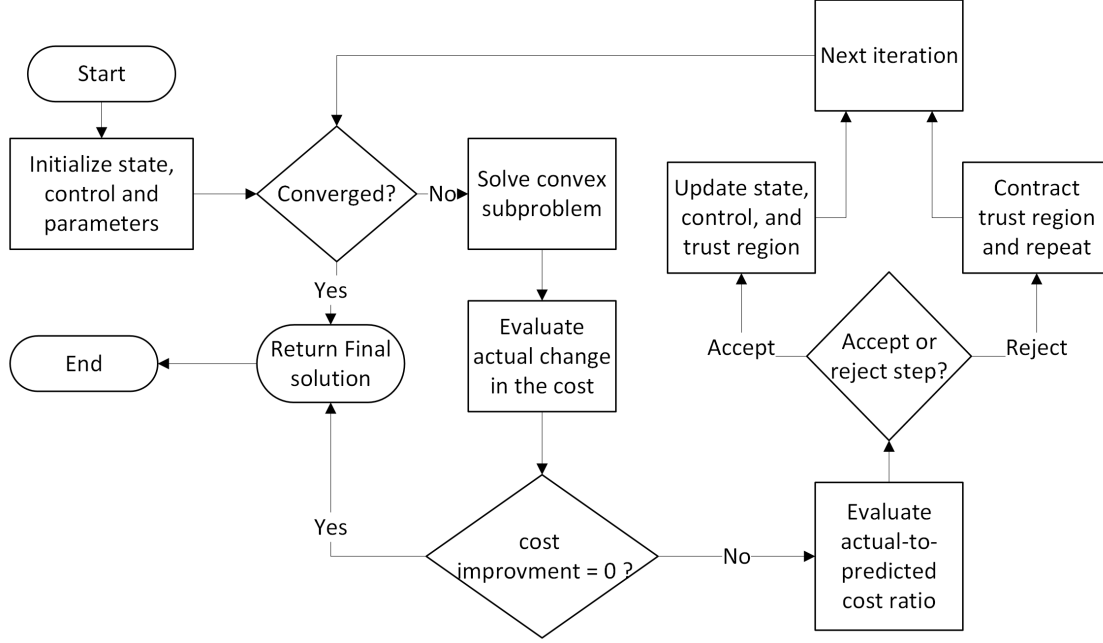


Fig. 1 SCvx algorithm high-level flow chart

A. Overview of Successive Convexification

This section gives a high-level overview of the SCvx algorithm. A detailed discussion can be found in Ref. [12]. As shown in Figure 1, the algorithm starts by initializing the state, control, and parameters. It then checks whether the solution has converged. If it has not, the algorithm solves a convex subproblem and computes the actual change in the cost. Next, it checks whether the cost improvement is zero. If the improvement is zero, the algorithm stops and returns the final solution. Otherwise, it calculates the ratio between the actual and predicted cost change by the convex subproblem to decide whether to accept or reject the step. When the step is accepted, the algorithm updates the state, control, and trust region and moves to the next iteration. When the step is rejected, the trust region is reduced and the process repeats. This loop continues until convergence, ensuring that each iteration either improves the solution or adjusts the trust region to maintain stable progress toward the optimum.

B. Integration of SCvx Algorithm with POST2

This work aims to determine the hypersonic entry trajectory that targets azimuth, velocity, downrange and crossrange at desired altitude as discussed in the earlier section using the SCvx approach within POST2. Several external tools developed in several languages, such as C++ and Julia, can facilitate the SCvx algorithm setup. This work considers the Julia toolbox developed by the Autonomous Controls Laboratory at the University of Washington [13]. The entry trajectory optimization problem is modeled to solve using the SCvx within the Julia toolbox and made into a library, which can be called from POST2. In addition, this work aims to develop a POST2 and SCvx interface. This interface initializes the SCvx using the POST2 simulation states and user defined input settings. In addition, this interface uses the optimal trajectory determined using the SCvx as the reference profile and issues bank commands to the POST2 outer-loop. To verify the implementation, in this work, the POST2 outer-loop simulation is modeled with the same fidelity as the SCvx trajectory optimization setup. The high-level setup of the interface between the SCvx and the POST2 is depicted in Figure 2. The developed interface will also handle any coordinate system and frame transformations required between the SCvx and POST2.

V. Numerical Simulations

This section presents numerical simulations of hypersonic entry trajectories determined by solving the optimization problem discussed previously using the SCvx algorithm, which generates bank commands for vehicle control in

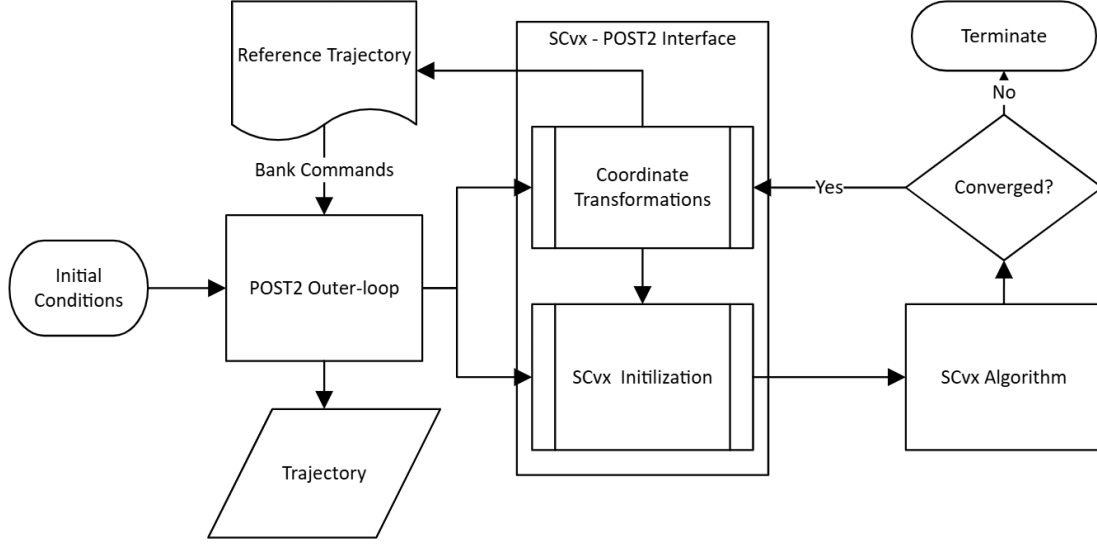


Fig. 2 SCvx interface with POST2

POST2. The section begins with a discussion of the SCvx algorithm and POST2 configuration settings employed in these simulations. This is followed by a discussion on the parametric fitting of the atmospheric and aerodynamic surrogate models utilized in the analysis. To verify the successful integration of SCvx within POST2, both simulation environments employ identical surrogate models. Finally, this section presents both nominal trajectory performance and Monte Carlo analysis results for the SCvx optimized trajectories in POST2.

A. Simulation Settings

This section will discuss the settings used within the SCvx and the POST2 simulation to generate the numerical simulations presented in this work. The initial conditions are obtained from the M2020 reconstruction trajectory [14]. The same initial states are used for the POST2 simulations and the trajectory optimization problem. In addition, to the initial states the final values for the radius, latitude, longitude, velocity and azimuth are also provided to the trajectory optimization problem. The initial and the final states used in this work are shown in Table 1. The mass of the vehicle for the nominal case is considered to be 3368.5 kg. The reference area for the vehicle is 16.02 m². For the trajectory optimization problem solved using the SCvx, the final time is considered to be bounded between 75 s and 90 s. There are also constraints on the bank angle to be between -180 deg and 180 deg. The control input, which is the bank rate, is considered to be between -20 and 20 deg/s. The SCvx algorithm takes several parameters [13] as inputs. In this work, the maximum iterations are set to 20 and the 100 nodes are considered for the trajectory optimization. SCvx solves a convex subproblem for each iteration, which propagates the dynamics and in this work 25 integration steps are considered for this propagation. SCvx has a single scalar weight used to scale the virtual control introduced for the successive convexification. A scalar weight of 5000 is employed in this work, tuned to ensure SCvx convergence. The SCvx algorithm adaptively changes the radius of the trust region using the ratio of change in the actual cost and change in the predicted convex cost ($\frac{\Delta J}{\Delta L}$). In this work, the trust region is shrunk by a factor of 0.8 if $\frac{\Delta J}{\Delta L}$ is less than 0.2 and is grown by 1.25 if $\frac{\Delta J}{\Delta L}$ is more than 0.8. The current iteration is rejected in this work if the $\frac{\Delta J}{\Delta L}$ is less than zero and the trust region is shrunk by 0.8. The initial trust region is considered as 0.1 and bounded to be between 0.001 and 1. The tolerance on the dynamic feasibility is considered to be $1e^{-6}$ and the tolerance on the change in the cost function used to check if the SCvx should terminate is considered to be $1e^{-3}$. The density and aerodynamic coefficient's polynomials used for both the POST2 simulation and the trajectory optimization problem solved using the SCvx is discussed in detail in the following section.

B. Parametric fitting of surrogate models using M2020 data

This section discusses the order and the data used for the parametric fitting of the surrogate models used in this work to estimate the density and aerodynamic coefficients.

Table 1 Initial and final states used for the POST2 simulation and the trajectory optimization problem solved using the SCvx.

State	Initial	Final
Velocity (m/s)	5355.4	1100
Flight-path Angle (deg)	-13.30	Free
Azimuth Angle (deg)	102.06	106.42

1. Density Fit

The order of both numerator and denominator polynomials is adjusted to achieve better fitting accuracy to the mesoscale data used for the M2020 simulations [15]. Higher-order polynomials providing more degrees of freedom to capture complex atmospheric structure are used at the cost of increased computational complexity. In this work, both the numerator and denominator in Equation (5) are considered to be of fourth-order polynomials ($m = n = 4$). The complete rational function becomes:

$$\ln(\rho(h)) = \frac{c_0 + c_1h + c_2h^2 + c_3h^3 + c_4h^4}{1 + b_1h + b_2h^2 + b_3h^3 + b_4h^4} \quad (9)$$

where $\{c_0, c_1, c_2, c_3, c_4, b_1, b_2, b_3, b_4\}$ are the fitted coefficients determined through nonlinear least squares optimization. The b_0 is considered as 1 in this work. Figure 3 compares the fitted polynomial with the mesoscale density data.

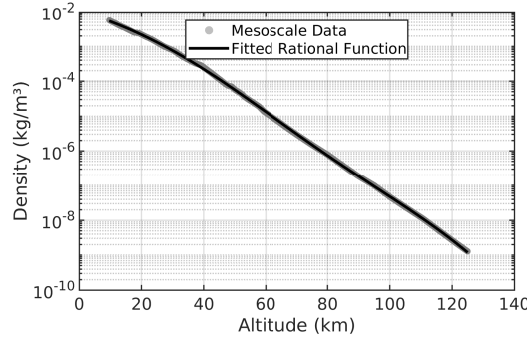


Fig. 3 Density - altitude rational function fit.

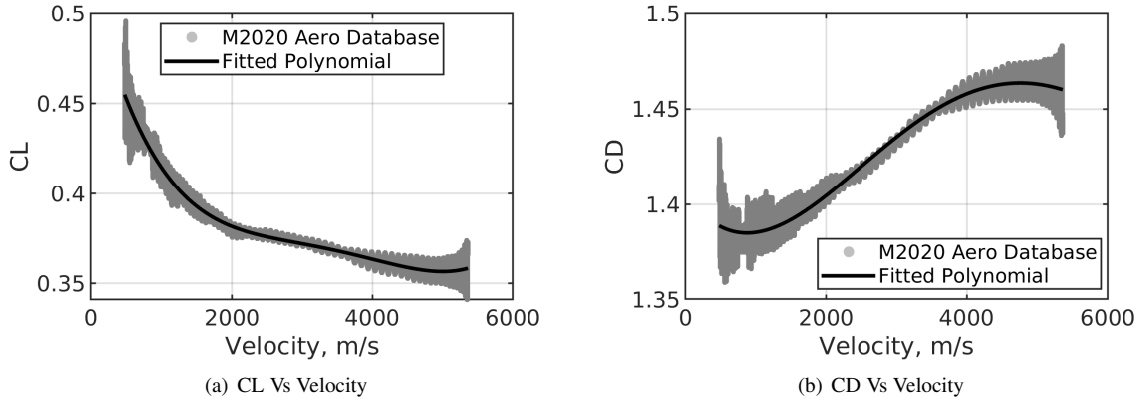


Fig. 4 Lift and drag coefficient fit using the data from the M2020 aero database.

2. Lift and Drag Coefficient Fit

For this study, fourth-order polynomials ($n = 4$) are employed:

$$C_L(v) = \alpha_0 + \alpha_1 v + \alpha_2 v^2 + \alpha_3 v^3 + \alpha_4 v^4 \quad (10)$$

$$C_D(v) = \beta_0 + \beta_1 v + \beta_2 v^2 + \beta_3 v^3 + \beta_4 v^4 \quad (11)$$

The polynomial order can be increased if the aerodynamic data exhibits more complex nonlinear behavior that requires higher-order terms for accurate representation. The coefficients are determined by minimizing the sum of squared residuals between the polynomial predictions and the reference aerodynamic data from the aero database of the aeroshell used for the previous Mars missions [16]. The data from the aero database oscillates as the vehicle's angle of attack varies as shown in Figure 4. As the attitude dynamics are not modeled within the three degree-of-freedom optimization problem formulation, a smooth polynomial of the aerodynamic coefficients should suffice. Figure 4 shows the fitted polynomials used to estimate the lift and drag coefficients within the optimization problem formulation.

C. Comparing nominal performance with M2020 reconstruction

Here, using the simulation settings, aerodynamic and atmospheric surrogate models discussed in the previous section, the optimization problem is solved with the SCvx algorithm integrated within POST2. The resulting bank angle profile serves as a reference trajectory for the POST2 simulation. For this validation study, the outer-loop POST2 simulation employs the same models used in the SCvx trajectory optimization problem. This consistent modeling approach enables direct comparison between trajectories and validates the optimization problem formulation. While the POST2 outer-loop simulation could incorporate higher-fidelity components such as six degrees-of-freedom dynamics, thruster models, sensors models, navigation filters, aerodynamic databases, and engineering atmospheric models like the GRAM suite [17], maintaining equivalent model fidelity between the SCvx optimization and POST2 outer-loop simulation is essential for verification purposes. This matching fidelity allows for meaningful comparison between the outer-loop trajectory and the optimal solution generated by SCvx, thereby validating the SCvx implementation within POST2. Using the SCvx solution as the reference trajectory, POST2 issues the bank commands to the outer-loop trajectory using linear interpolation and is developed as part of the SCvx-POST2 interface. As POST2 integrates the equations of the motion in the inertial frame and the optimization problem considers the equations of motion in terms of the planet-relative states, matching these trajectories also ensure any required frame transformations are done accurately.

Figure 5 compares the POST2 simulation trajectory with the initial guess and final solution from the trajectory optimization problem, alongside the range control portion of the M2020 reconstruction best estimated trajectory. The comparison includes radius, velocity, latitude, longitude, flight-path angle, and azimuth angle. The definitions of these states is consistent with the ones described in the Section III.A. As described in the optimization problem formulation, the final values for radius, latitude, longitude, velocity, and azimuth are constrained. The final radius, velocity, latitude, and longitude are fixed to match the M2020 reconstruction trajectory's best estimate at the end of range control. The final azimuth value is set to match the M2020 reconstruction trajectory's best estimate at the end of the subsequent heading alignment phase. For Mars missions, the vehicle transitions from range control to heading alignment phase, where it steers toward the target while maximizing altitude for parachute deployment. By targeting the selected latitude, longitude, and azimuth angle at the end of range control, the vehicle achieves the desired downrange, crossrange, and heading alignment objectives. Since the vehicle is already oriented toward the target at the end of range control, the bank angle during the heading alignment phase can remain at zero degrees for nominal trajectories, thereby maximizing altitude for parachute deployment. This heading alignment is critical because the vehicle has no active control authority after parachute deployment.

The initial guess for the trajectory optimization shown in Figure 5 is generated by propagating the optimization dynamics with a constant bank angle of 70° . This approach provides an effective initial guess, as evident from Figure 5, where the initial trajectory is relatively close to the final solution compared to alternative initialization methods such as linear interpolation between the initial and desired final states. The final optimization solution matches closely with the POST2 simulation trajectory, demonstrating successful integration of the SCvx algorithm within POST2. Additionally, the SCvx solution aligns well with the M2020 reconstruction trajectory's best estimate, validating the effectiveness of the atmospheric and aerodynamic surrogate models employed in this work. Although the final flight-path angle is unconstrained, it approaches zero at the end of range control, similar to the M2020 reconstruction trajectory. This behavior is beneficial because higher flight-path angles after range control help maximize the vehicle's altitude at parachute deployment. The final time is unconstrained for the optimization problem and as one can see the final time at the end of the range control matches very closely with the M2020 reconstruction trajectory's final time.

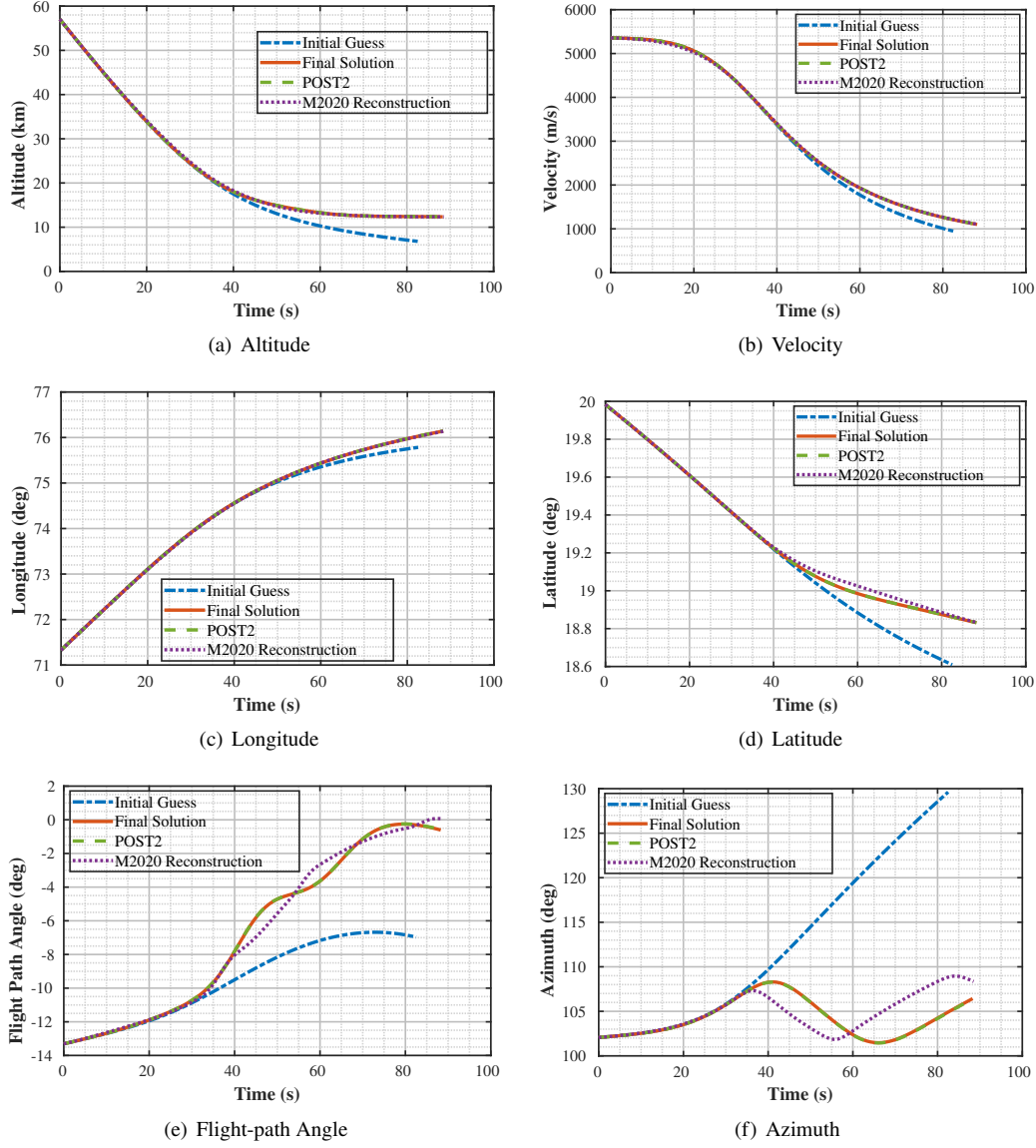


Fig. 5 Trajectory from POST2 simulation compared with initial guess, final solution and M2020 reconstruction data

Figure 6 presents a comparison of the bank angle and bank rate profiles. As noted previously, a constant bank angle is used to generate the initial guess for the trajectory optimization problem. The comparison between the SCvx final solution's bank angle profile and the POST2 simulation demonstrates the accuracy of the interpolation scheme developed for SCvx and POST2 integration. The M2020 bank profile, which incorporates feedback control, is included for qualitative comparison only. Unlike the M2020 range control guidance that uses lateral dead bands to trigger bank reversals, the SCvx solution determines the bank profile to simultaneously target the desired crossrange and downrange without such constraints. Since the POST2 simulation in this work considers only three degrees of freedom, the bank rate is computed using finite differencing of the POST2 bank profile to enable comparison with the SCvx solution's bank rate, which serves as the control input for the optimization problem. The SCvx solution minimizes bank rate usage, operating significantly below the maximum allowable bank rate of 20 deg/s, thereby demonstrating the effectiveness of trajectory optimization using SCvx. The non-zero final bank angle at the end of range control can be addressed during the subsequent heading alignment phase.

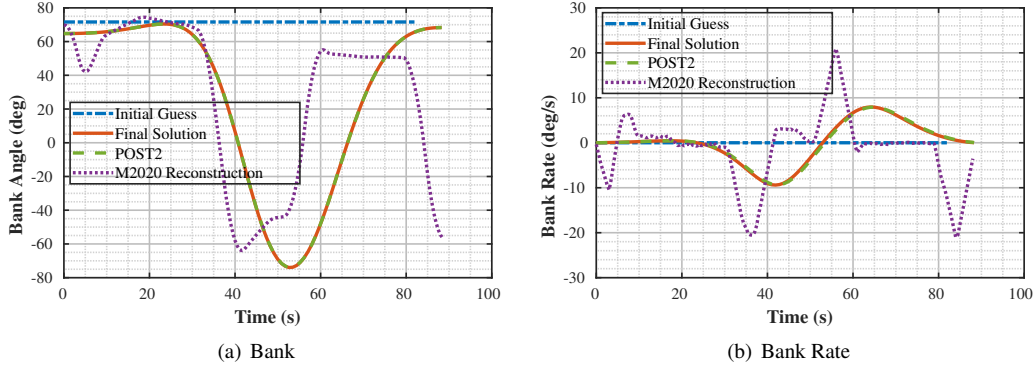


Fig. 6 Bank and bank rate profiles from POST2 simulation compared with initial guess, final solution and M2020 reconstruction data

Table 2 Normal distribution dispersions of initial states used for the Monte Carlo simulations to verify the robustness of the SCvx within POST2

Initial State	3-Sigma Value
Radius	1302.87 m
Latitude	0.0198 deg
Longitude	0.0972 deg
Velocity	1.0401 m/s
flight-path Angle	0.0630 deg
Azimuth Angle	0.0385 deg
Mass	14.9763 kg

D. Monte Carlo performance

The SCvx-POST2 interface developed in this work enables Monte Carlo simulations where each case solves a trajectory optimization problem using SCvx to determine the reference trajectory. For the Monte Carlo analysis, the initial states and mass are dispersed across 8,000 cases. The initial states follow normal distributions with means equal to the nominal values in Table 1 and 3-sigma values shown in Table 2. The standard deviation values are derived from previous POST2 M2020 Monte Carlo simulations using the data at the beginning of range control. Note that these values differ from the much smaller standard deviations in M2020 trajectory reconstruction data. The final targets at the end of range control remain constant across all cases, as shown in Table 1.

In typical EDL missions, the ground navigation team establishes a data cutoff time and uses all available measurements to estimate the current vehicle state. Based on this state knowledge, guidance parameters are adjusted and transmitted to the spacecraft via parameter updates. To allow sufficient processing time, ground teams typically set the data cutoff several days before entry interface. Recent navigation advances enable spacecraft to estimate states autonomously onboard, potentially providing more accurate position knowledge by processing additional available data. In such scenarios, ground-in-the-loop parameter updates for guidance (such as reference trajectory updates) may become impractical, and algorithms like SCvx can determine reference trajectories using more accurate autonomous navigation solutions. This capability motivates the Monte Carlo approach used in this work, which focuses on dispersing initial states. Note that uncertainties in atmospheric conditions, aerodynamics, and other disturbance sources require feedback control and cannot be addressed solely by recomputing the reference trajectory before entry. Therefore, these uncertainties are not considered in this work.

Figure 7 presents the statistical distribution of states fixed for trajectory optimization at the end of range control, specifically showing altitude, velocity, latitude, longitude, and azimuth angle. Additionally, the statistics for the final time of trajectory optimization are included. The figure displays results only for Monte Carlo cases that produced dynamically feasible trajectories with the final subproblem solved without errors. Of the 8,001 cases analyzed, four cases could not be solved by SCvx. For the remaining 7,997 successful cases, the final states from POST2 simulation exhibit

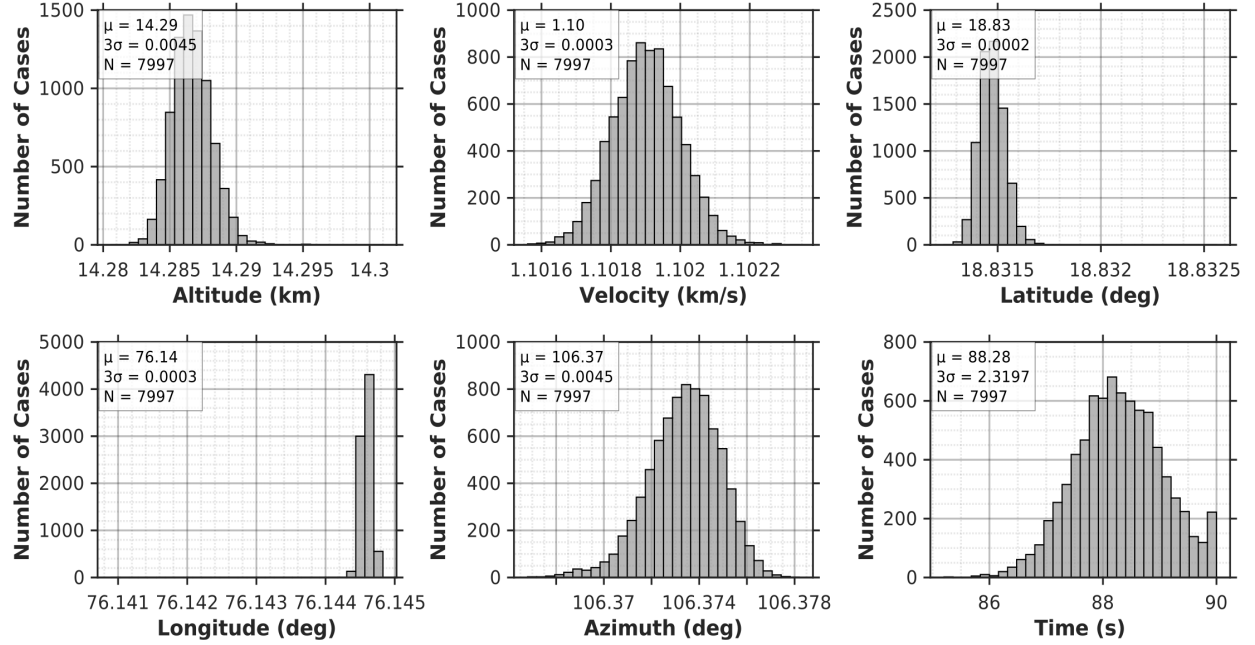


Fig. 7 Statistics of altitude, velocity, latitude, longitude, azimuth and time at the end of the range control

very small standard deviations, as expected, demonstrating the effectiveness and robustness of the SCvx algorithm. All Monte Carlo cases used identical SCvx parameters and initial guess generation methods as the nominal case, with no manual tuning required. This approach proved efficient across all simulated scenarios. The variation in final time across different Monte Carlo cases accounts for the differences in initial states, as the optimizer adapts the trajectory duration to accommodate the dispersed starting conditions. To understand the four failed cases, the correlation between dispersed initial state values and convergence failure was analyzed. This analysis reveals a strong correlation between initial latitude and longitude dispersions and solver failure, as shown in Figure 8. Since the optimization problem enforces strict constraints on final latitude and longitude (downrange and crossrange), initial conditions that deviate significantly from target values prevent convergence. This limitation could be addressed in future work by reformulating the optimization problem with soft constraints on latitude and longitude positions. Additionally, if a minimum bank angle margin is desired for feedback control implementation, the bank angle limits in the SCvx reference trajectory optimization can be adjusted accordingly.

VI. Conclusion

This work demonstrates the successful integration of the Successive Convexification (SCvx) algorithm for trajectory optimization within the Program to Optimize Simulated Trajectories II (POST2) flight simulation tool. To validate this integration, this work modeled hypersonic entry at Mars similar to the range control portion of the Mars 2020 mission. The trajectory optimization problem was implemented using a Julia toolbox developed by the Autonomous Controls Laboratory at the University of Washington and compiled into a library callable from POST2. To ensure accurate validation, the outer-loop POST2 simulation was configured to use models of identical fidelity to those employed in the SCvx trajectory optimization problem, while implementing the bank angle profile from the SCvx solution as a reference through linear interpolation. The results confirm successful integration, with the final optimization solution from SCvx closely matching the POST2 simulation trajectory. Using SCvx and initial states similar to the Mars 2020 trajectory, POST2 simulation generated a three degrees-of-freedom trajectory qualitatively comparable to the Mars 2020 reconstruction trajectory. Furthermore, this work demonstrates the robust Monte Carlo analysis capabilities of the developed SCvx-POST2 interface. Through an 8,000-case Monte Carlo simulation with dispersed initial conditions, this work established the robustness of the SCvx algorithm, which achieved over 99.9% convergence rate. The SCvx-POST2 interface developed in this work enables high-fidelity POST2 simulations to generate reference trajectories using the computationally efficient SCvx algorithm (within 20 iterations), providing a valuable tool for future Entry, Descent, and

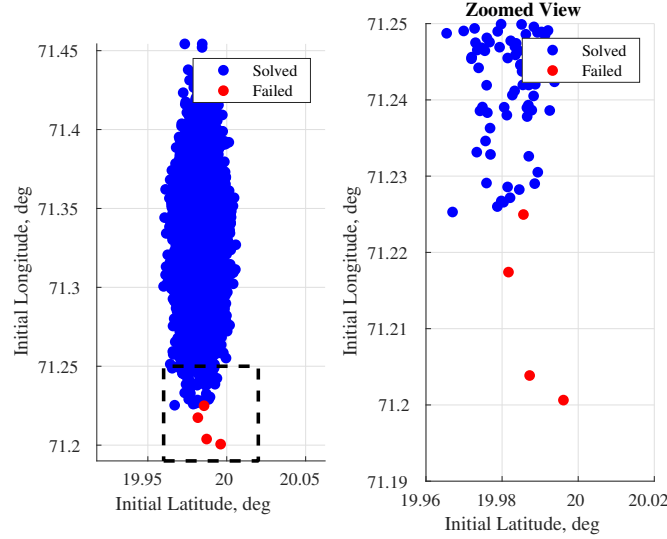


Fig. 8 Initial latitude and longitude values at the beginning of the range control used for the Monte Carlo analysis

Landing mission analysis. Future work could extend this approach by using the SCvx-generated reference trajectories for trajectory tracking or terminal control feedback gain computation.

VII. Acknowledgments

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